Chartering Predictive Analytics: A Case Study

Full paper

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Abstract

Many organizations are implementing analytics projects. Unfortunately, most big data projects fail, and the reasons are not well understood (LaValle et al. 2013). This paper studies the chartering phase of a predictive analytics project to further our understanding of big data projects. We conduct a qualitative study at a large supply chain company. We employ a variety of qualitative research techniques, including participant observation and interviews of key project personnel. In particular, we conduct a case study of the company's predictive analytics journey and the challenges it encountered. These include corporate governance, vendor relationships, and lack of data. This research adds insight into why companies implement predictive analytics projects and the challenges they face. The study makes several contributions to the IS literature by adding a qualitative perspective to the big data field, which is dominated by quantitative studies, and focusing on the chartering phase of project implementation.

Keywords big data, predictive analytics, shadow IT, project chartering, vendor selection

Introduction

Big data is widely viewed as a panacea for a host of business problems. An example is fraud detection in the finance industry (Phua et al. 2004). In addition, big data has the potential to create a competitive advantage for an organization (Bose 2009). However, most big data projects fail, and the reasons for the failures are not well understood (LaValle et al. 2013). The purpose of this study is to understand the chartering phase of a big data project, specifically a predictive analytics project. We adopt Shmueli and Koppius (2010)'s definition of predictive analytics as "statistical models and other empirical methods that are aimed at creating empirical predictions, as well as methods for assessing the quality of those predictions in practice, i.e., predictive power." This paper will shed light on the motivations for considering predictive analytics projects and the dynamics that impact an organization's decision to move forward with predictive analytics.

The discussion around big data has evolved. The definition of big data has largely settled on the four Vs – volume, velocity, variety, and veracity (Ward and Barker 2013). For this study, we adopt the definition of big data as "the derivation of value from traditional relational database driven business decision making, augmented with new sources of unstructured data" (Dijcks 2012). Debates on whether big data is a new phenomenon have generally subsided. It is true, however, that the question of what exactly constitutes *valuable* big data remains open. The ever-decreasing cost of storage, the advent and rise of social media, and increasing network bandwidth have resulted in companies accumulating large volumes of data (Chen et al. 2012). Increasingly, companies seek to exploit the data in their ownership and extract value from it. However, the skills to effectively exploit big data are in short supply (McAfee et al. 2012). Without the requisite skill-set, companies are unlikely to be able to distinguish between valuable and worthless big data, and they are also unlikely to extract value from valuable big data.

Because of the specialized nature of big data projects, we expect companies to invite external vendors to accomplish their projects. This is especially true of companies whose core focus is not information systems (hereinafter IS) (Ross and Weill 2002). The selection of vendors is, therefore, an important consideration in the implementation of big data projects. This area of research has received limited focus in the literature. However, vendor selection in big data projects is an important topic to study because selecting the wrong vendor may lead to project failure. Therefore, the research gap that we seek to address is vendor selection in the arena of big data projects.

Our research takes a qualitative approach to big data projects and will answer two research questions. Why do organizations consider implementing a big data project? In this case, the project is a predictive analytics project. What factors impact their decision to move forward with or to abandon the project? We employed qualitative research in the study in order to observe how the vendor selection process unfolds. This enabled us to understand the context within which the decision-making process occurs (Myers 2013). Qualitative research would help supply some much-needed richness to the phenomenon of big data implementation, thereby allowing for explanatory theory-building (Eisenhardt 1989).

Literature Review

Thus far, research on predictive analytics in IS has fallen under the purview of big data. The research on big data and predictive analytics in IS journals has generally fallen into two camps: first, a preponderance of research focuses on how companies can successfully employ big data to answer IS research questions such as whether an individual's emotional mood can be affected by his/her social media friends (Agarwal and Dhar 2014; Shmueli and Koppius 2010). In this regard, researchers view big data as a method that can illuminate certain phenomena such as large-scale emotional contagion and other social experiments that are relevant to the field (Kramer et al. 2014). The second camp focuses on how companies can actually operationalize big data in solving business problems, and is the focus of this study.

Existing research has focused on some of the challenges the proliferation of data has introduced. For example, Tallon et al. (2013) explored the complexity involved in managing extreme amounts of data. They found that adoption of effective information governance practices can help boost company performance. Other research has focused on ascertaining the value of a company's data (Tallon 2013). According to Tallon (2013), even the most data-rich companies do not report the value of their data on the balance sheet, which essentially translates to data having non-existent value. However, no one can argue that company data is essentially worthless. Incidents such as data breaches and data loss frequently result in financial loss, hence, company data has value (Acquisti et al. 2006).

While previous studies have done an excellent job of identifying the more obvious problems associated with big data, there remain some unarticulated problems. For example, big data has widely been defined with the three Vs, volume, veracity, and variety, and recently, some scholars have begun to add a fourth V for value (Ward and Barker 2013). However, the question of how to define data with only a subset of the four Vs remains unanswered. This is a problem because companies with large volumes of data are likely to regard it as big data, whether the other V's exist or not. In addition, there are few concrete statements on how much data actually constitutes big data (Ward and Barker 2013). The question of value is also largely unanswered, because how value is extracted from big data should vary across companies, and across industries.

We employ process theory, which posits that antecedents are necessary but not always sufficient conditions for outcome success, to understand the chartering undertaken by the organization (Koh et al. 2000). In other words, according to Koh et al. (2000), "the outcomes can happen only under these conditions, but the outcomes may also not occur even when these conditions are present." In our case study, we want to determine first whether there are sufficient conditions for the predictive analytics project to succeed.

The key ingredients for success in enterprise resource planning projects (hereinafter ERP projects) may also be relevant for predictive analytics projects. To be successful, predictive analytics projects require end-user involvement, IS skills, and management commitment to the implementation effort. Consistent with Koh et al. (2000)'s interpretation of process theory, although the above conditions may be present at the start of a predictive analytics project, it is possible for the project to fail owing to contingencies along the project implementation process. Further, Markus and Tanis (2000) identify four stages of a project lifecycle: chartering (all activities and decisions leading towards the funding of the project), project implementation (configuration and rollout of the project), shakedown (elimination of system bugs), and upward and downward (maintenance and support of the system). We observe that certain projects may never advance from the chartering phase, and hence, our study examines the factors that determine whether a project moves from the chartering to the project phase.

Research Method

Research Context

We are conducting this study at a supply chain company that is exploring how predictive analytics could help its business. As the industry leader, SupplyChainCo, a pseudonym, has nearly $50 billion dollars in annual sales and over 10,000 employees. SupplyChainCo's business model is buying and delivering groceries. Merchandising employees buy groceries that are delivered to more than 50 warehouses throughout the United States. Warehouse employees pick the groceries and load them on trucks, which deliver the groceries to thousands of retailers and restaurants. A corporate headquarters supports warehousing and logistical operations nationwide. The largest corporate departments are Merchandising and Information Systems (hereinafter IS). IS provides the systems that support Merchandising and the rest of SupplyChainCo's operations. All IS functions are centralized and SupplyChainCo uses Oracle as its ERP system. Because SupplyChainCo "makes pennies on each order[1]" the company is cost-conscious. Most IS projects focus on cost reduction and efficiency improvements.

For this research, we chose SupplyChainCo for theoretical sampling reasons (Patton, 1990). SupplyChainCo's Special Operations department (hereinafter SpecOps) was exploring the potential benefits of implementing a predictive analytics (i.e., big data) project. We were interested in learning more about the chartering phase of predictive analytics projects and learning about user-driven IS projects. Since SpecOps is an independent department separate from both the IS and Merchandising departments, we thought their foray into an IS project for the Merchandising department would be interesting. SpecOps focuses on special projects that bring revenue into the company. Since its formation nearly a decade ago, the department has brought in nearly half a billion dollars to the bottom line. Typical projects deal with "buying low and selling high." SpecOps studies when product prices are likely to increase and then advises Merchandising to overbuy products so that SupplyChainCo makes a holding gain.

Data Collection

Data collection for this study began in May 2015 and is still underway. The senior vice president in charge of SpecOps at SupplyChainCo allowed us to conduct fieldwork at the company. This gave us immediate legitimacy and credibility with the interviewees (Patton 1990). The senior vice president asked the manager responsible for the predictive analytics project to invite us to meetings, allow us to review status reports and conduct interviews. Because this was the first time that SpecOps had hired IS employees, it required the two employees working on the project to keep weekly status reports. Every Friday afternoon the IS analysts reported their progress to management. The reports addressed accomplishments, lessons learned, challenges and goals for the following week. We reviewed these reports monthly and conducted a focus group with the analysts working on the project. We also conducted follow-up interviews with the analysts and the manager in charge of the project. The status reports combined with the follow-up interviews exemplify the diary interview method (Zimmerman and Wieder 1977). This method helped us to understand what was going on with the project and to tailor our interviews to each interviewee's role and experiences. In essence, those who kept the diaries became adjunct ethnographers (Zimmerman and Wieder 1977).

The in-person meetings we observed were between predictive analytics vendors and SpecOps. During the initial vendor meeting, the SpecOps' manager laid out the project. The vendor pitched their solution during the follow-up meeting. Most meetings included SpecOps' senior vice president, director and the manager in charge of the predictive analytics project. Each vendor brought a technical person and a business development person to the meeting. We have copies of the vendors' presentations along with internal presentations and internal emails regarding the project. Since this project is ongoing, we receive periodic updates on the project. We selected these methods of data collection because they occurred in a

[1] Quotes in the text come from the field notes.

natural environment, and they combined to create a holistic picture of the vendor selection process (Marshall and Rossman 2011). The different sources of data also allowed for triangulation, so that we were not reliant on only one source for information (Myers 2013). Table 1 outlines the data collected to date.

	Number	**Length**	**Date**
Weeks Status Reports	12	1 page	May -August 2015
Focus Groups	4	60-120 minutes	May -August 2015
Predictive Analytics Vendor Meetings	2	90 minutes	January 2016
Interviews-Semi-structured, recorded and transcribed	4	1-4.5 hours	February 2016

Table 1. Data Collection

Interpretivist Perspective and Data Analysis

Two dynamics made an interpretive approach ideal for this study (Klein and Myers 1999). First, organizations are in the early stages of embarking on big data projects like the predictive analytics project in this study (LaValle et al. 2011). Second, our knowledge surrounding user-initiated IS projects that span outside a user's workgroup is limited at best (Spierings et al. 2011). Our interpretive approach allows us to gain rich and deep insight grounded in the organizational context and the accounts of the employees involved with the project (Madill, Jordan et al. 2000). Consistent with guidelines on conducting interpretive case studies, we did not impose an a priori theory on our data nor did we test a theoretical framework (Walsham 1995, Walsham 2006). Rather, we made sense of our data using open and focused coding (Urquehart 2013). This allowed us to identify initial concepts and then link the evolving set of concepts to higher level categories. We used QSR NVivo 11 to organize our emerging coding scheme. The case section, which follows, elaborates on some of our categories. To assess our research approach, we rely upon Klein and Myers' (1999) principles of interpretive research, which have become the standard for evaluating interpretive case studies in IS.

Case: Chartering Predictive Analytics at SupplyChainCo

This case analysis will discuss why SupplyChainCo considered a predictive analytics project, how they initiated it, and the factors impacting their decision to move forward with the project.

The decade-old Special Operations (SpecOps) group at SupplyChainCo was a unique department with no responsibilities except expanding company profits. Their focus was to find and implement innovations that created additional profit or value for the company. Because regular departments were focused on their primary tasks, SupplyChainCo believed that a separate group, without day to day responsibilities, was needed to find the innovations that people were too busy or too close to a problem to see. As a revenue generating department, SpecOps held an enviable position in the company. SpecOps staff were given favorable responses to their resource requests, regardless of expense. They also commanded respect from other departments, and requests were often speedily fulfilled, with a few notable exceptions. Merchandising, one of the departments that shared in the dollar successes and subsequent bonuses provided by SpecOps projects, was generally cooperative with SpecOps in the pursuit of the latter's revenue generating projects, but this was not always the case for other teams. An interesting aspect of SpecOps was their shadow IS projects, which included the predictive analytics venture discussed in this case. The IS department at SupplyChainCo was focused on operations, maintenance, and user support. IS had little time, staff, or budget for challenging projects.

Project Description

The goal of the SpecOps department's project was to predict price changes. As a distributor, SupplyChainCo paid Price A, marked up the good, and sold it to the retailer. When wholesale goods increased in cost, retail price increases followed at the same markup percentage. However, when wholesale price increases could be predicted, SupplyChainCo could often purchase greater inventory at the old price and sell it at the new price, which was called an inventory holding gain. Building the predictive analytics systems involved looking at internal and external data. Internal data included product specifications (i.e., size, and weight), quantity sold, and price. By combining this data with external sources, such as weather events, agricultural problems, regulatory changes, commodity prices, and energy prices, SpecOps hoped to predict when the wholesale price of an item increases. While some products had prices that were linearly related, such as the direct relationship between beef prices and beef jerky, other relationships were not as clear.

Several aspects of the predictive analytics project made it a good candidate for success. First, SpecOps had manually produced price predictions for several products with great success, so there was some confidence that it could be done for at least some of the items. Second, SupplyChainCo had a low capital cost, therefore increasing inventory in hopes of a wholesale cost increase that did not materialize was a minor concern. The predictive analytics project manager commented, "Missing a price increase can mean hundreds of millions of dollars. If the predictive analytics project helps us get one price increase, the project has paid for itself many times over." Last, the company was not constrained by the cost of the system, because the benefits were so massive. On the other hand, SupplyChainCo's encountered several challenges during its journey into predictive analytics.

SupplyChainCo's Predictive Analytics Journey

The data analytics project began in May of 2015. A member of the SpecOps team shared, "Where did this idea come from? It came from the fact that we already do inventory holding gains on certain products." However, arduous manual searches could only be justified for a few highly profitable product groups, so the team hoped to produce similar results with predictive analytics for other product lines. As a manager explained, "The juice doesn't become worth the squeeze. You could spend the same number of man hours looking at (another product), but your inventory holding gains are not going to really justify 3000 man hours."

Management assigned a SpecOps manager to lead the project and hired two IS analysts to assist with project validation and vendor identification. Initially, management tasked the analysts with quantifying how much money SupplyChainCo could have been made with perfect information. They based their research on historical data from June of 2010 to June 2015 and attempted to estimate the upper and lower bounds of profitability for inventory holding gains. The analysts worked with three Merchandising managers to build their data and gather insight on the causes of price increases. The resulting data had 9.8 million rows and became too much for the existing Excel and Access software that was available, resulting in fractured data views. However, the analysts were able to come up with "the perfect knowledge model," which assumed maximum possible profit from holding gains, maximum inventory held before the price change, and controlled for limitations such as perishability, limited warehouse space, and holding costs.

After the analysts presented the model to executive management, the potential returns on the project were enough to convince the company that the project warranted more investigation. At this point, vendor identification began. The analysts searched for the top predictive analytics companies on Gartner research and discovered seven vendors. The analysts emailed these seven vendors but received only five replies. The predictive analytics team interviewed these companies by phone. During the interviews, some of the vendors expressed concerns such as compatibility with SupplyChainCo's existing IS architecture, the ability/willingness to create a custom solution, and lack of technical knowledge on the part of some of the sales people. An analyst said, "(the vendor) response was 'Great, great, great, great your project sounds amazing and we've already built a tool to solve it.' Really what they were saying is they have a pre-built tool that you can use and they think that their pre-built tool will solve the problem. They weren't going to create a model specific for us… and they said 'We want to sell you our out-of-the-box product.'"

After the phone interviews, the SpecOps vendor list shrank to three competitors. Vendor A was the industry leader in predictive analytics, and although they had not previously done a project exactly like this, their significant experience and resources put them at an advantage. Vendor B, which was an early favorite due to their local office and their ease of integration with SupplyChainCo's architecture, soon extinguished enthusiasm with a series of missteps, such as trying to sell "what they had" instead of what SupplyChainCo wanted. "This is where (they) shot themselves in the foot, when (they) came back to us, they…said, 'The use case you told us was great but we want to solve this other problem,' which went over like a ton of bricks." This mistake was overcome, but legal problems over SupplyChainCo's vendor non-disclosure agreement (NDA) soon aggravated the situation. Vendor C was "a small fish relative to the other players" and offered an existing product that they hoped could be slightly modified to provide a solution. At this point, Special Ops offered the three vendors a chance to submit a proof of concept.

Proof of concept

The goal of the proof of concept analysis was to test the vendors and see if they could predict price increases. SpecOps gave each vendor five years of data for forty items that were representative of SupplyChainCo's inventory. Approximately 20% of the data had three or more price changes, and the 80% majority had only two or one. The goal was for the vendor to take the data and determine what external factors influenced price changes and when. SpecOps knew the answers to the questions for this data, they just wanted to see if the vendor could come up with the same answer before hiring them.

The results of this effort disappointed the SpecOps team. Vendor B had delays with the NDA and could not present their findings until the NDA was signed by both parties. As of this writing, five months had passed since the issue first arose. Vendor C, despite sending three company representatives across the country to attend the presentation, fell short due to their product limitations. They were able to find some interesting relationships between commodities and price increases, but little of their work was of value to SupplyChainCo. Vendor C admitted they could not perform the project as outlined, but still wanted to work with SupplyChainCo on a variation of it that their system could address. Vendor A stated that they could not create a viable model with the 40 SKUs, although they still believed the project was feasible. They suggested that focusing on product groups instead of individual SKUs might yield better results. At any rate, Vendor A would not provide further analysis unless SupplyChainCo agreed to pay. They planned to return in a month for a presentation with management to pitch their plan. When comparing the three vendors, SpecOps identified several key points for evaluation. See Table 2.

	Vendor A	**Vendor B**	**Vendor C**
Local office	No	Yes	No
Access to the external data needed	Yes	Yes	Yes
Supply chain experience	No	Yes	No
Ability to analyze qualitative and unstructured data	Yes	Yes, additional cost	Yes
Vendor analysts available	Yes	Yes	Yes
Works with existing architecture	Yes	Yes	Yes
Ability to create a custom solution	Custom	Ability to do custom but preferred to use out of the box solution	Out-of-the-box solution, did not perform

Table 2. Vendor Pros and Cons

Ironically, the only vendor that scored yes in all categories earned the worst score for service. Vendor B pushed a different solution and delayed the NDA signing. None of the complaints against this vendor were in the official list of concerns, yet the researchers were given the distinct impression that Vendor B was out of consideration. The predictive analytics manager told us, "From a business perspective they have handled themselves horribly. I just want to cut them because I can't stand dealing with them (Vendor B) anymore." After the next meeting with Vendor A, the team planned to reevaluate not only the vendors but if SpecOps should continue with the project at all. If no one could resolve the conundrum of too few data points, it could all be for naught.

Project challenges

While SupplyChainCo had high hopes for the predictive analytics project, several challenges threatened to derail it. First was a lack of internal expertise, followed by worries about vendor control. Conflicting performance goals between departments at SupplyChainCo also began to influence the project as they moved forward, as was the lack of available data points for price changes, despite a large number of records.

Challenge 1: Lack of Internal Expertise. SupplyChainCo lacked internal resources to work on the project, although the company did hire two short-term analysts with joint Masters of Science in Information Systems/MBA degrees to get it off the ground. Given the shortage of internal skills, the company decided that they needed a solution that would provide the manpower, as well as the system. Further, SupplyChainCo required any system to be premise-based, not cloud-based, due to security requirements, which further limited the talent pool to local recruiting. A SpecOps manager explained, "We typically get what I call our fire power outside the company. When we need to get a project done, we typically outsource the solution."

Challenge 2: Vendor Control. SupplyChainCo could build up inventory on products and the foundation of their predictive analytics project was stockpiling. SupplyChainCo's vendors (e.g., Hershey, Procter and Gamble) controlled the quantity sold to SupplyChainCo and many products, such as eggs, were perishable, and therefore self-limiting in terms of stockpiling. Additionally, manufacturers could see SupplyChainCo's inventory levels through supplier management systems, and sudden increases in orders could alert the former. An analyst mentioned, "Because they (the vendors) keep track of all inventory levels--if they notice that our inventory levels are spiking-- they cap the amount you can order. They start preventing you from building more inventory."

Challenge 3: Conflicting Performance Goals. A successful predictive analytics project would magnify the competing performance goals of the three departments involved in making the project a success. Of course, every department aimed to expand revenue and profits for the organization. While this was the only performance measure for the SpecOps group, Merchandising and IS employees had mid-range performance goals. Merchandising management penalized its buyers if they bought too much product, which was exactly what the predictive analytics project encouraged. Since IS evaluated its employees on cost control and budget management, the prospect of maintaining a predictive analytics system or supporting SpecOps in its efforts was unappealing.

Challenge 4: Lack of data points. This challenge came from a combination of the IS department's cost control policies and the existence of only a few price changes for many of the items SupplyChainCo supplied. SupplyChainCo's IS department believed that it was too expensive to store and save data after five years, therefore, it deleted data older than five years. This practice did not bode well for the predictive analytics project because many of the products changed prices only a few times in a five-year period. In the quote below a SpecOps manager laments about too few data points. "Look, guys, regression isn't working. You're going to have a very difficult time doing multivariate regression on our pricing data… your number of data points might be fewer than your degrees of freedom."

Discussion/Implications

This preceding case contributes to our understanding of the chartering phase of a predictive analytics project. Project chartering has received limited treatment in the literature and in IS graduate education (Du et al. 2004). Further, research on project chartering typically includes it as one of four phases of the ERP life cycle (Markus and Tanis 2000), the result being that chartering is rarely studied in isolation. Our study aims to address this important gap in the literature because it is important to understand the factors that potentially lead to project non-adoption. The literature generally reports success stories of predictive analytics projects; examining the chartering such process reveals the challenges that are faced by the company – specifically the lack of internal expertise, disputes with vendors, project control, conflicting goals among participating departments, and inadequate data. Our study provides insight into the key requirements that vendors need to fulfill – particularly their expertise. Compared to previous IS chartering research our study investigates an IS project chartered by a corporate department outside the IS department. This is important as the number of shadow IT, or feral information systems, is increasing at a rate 112% per year owing to the rise of cloud computing (Dunucci 2016).

By highlighting some challenges associated with moving forward with predictive analytics projects, our study adds insight into the predictive analytics literature that will help practitioners. Compared to typical IS projects, predictive analytics projects require rare specialized skills (McAfee et al. 2012). As a result, we expect that our qualitative study will shed light on the skills necessary to launch a predictive analytics project. Second, predictive analytics projects have the potential to complicate project governance in the organization. Data storage is a challenge associated with big data projects (Chen and Zhang 2014). Our case study shows that SupplyChainCo is not immune to this problem, because its IS department, constrained by its focus on cost reduction, has been forced to purge its data every five years. There is a need for companies to understand the value of their data because data is the most important input for predictive analytics projects. As illustrated by SupplyChainCo's data storage problem, if the project is initiated outside IT, intra-organization conflicts are likely to erupt. This is because IS at SupplyChainCo is evaluated on cost control, but the predictive analytics project requires that IS stops its data purging strategy. We conclude that big data may require rethinking performance objectives to align with the goals of the project. Specifically, the IS department's performance would need to be evaluated differently in order for it to participate willingly in the maintenance of the predictive analytics system.

Lastly, our study focused on the interactions between SupplyChainCo and vendors, and it yielded some surprising insights on the strategies adopted by vendors. First, some vendors were forthcoming in expressing their lack of ability to solve SupplyChainCo's problem. Vendor overpromising is a well-documented problem in the IS project literature (Grossman and Walsh 2004), hence, it is surprising that vendors in this predictive analytics project honestly expressed their shortcomings. Further, one of the vendors seemed combative, rather than accommodating to the stated wishes of the customer. Seemingly, the vendor's behavior was motivated by the need to protect its competitive secrets, a consideration that might be unique to predictive analytics projects. These findings suggest that predictive analytics projects could have dynamics that differ from ordinary IS projects because vendor behavior in this context is a radical departure from the behavior captured in the literature. These findings suggest that existing theories on IS projects require extension if they are to generalize to predictive analytics projects.

Conclusion

This study sought to understand why organizations consider implementing a big data project and what factors impact their decision to move forward. Our case analysis shows that SupplyChainCo started on their predictive analytics journey because management had learned about the potential benefits of analytics projects in other companies and envisioned that the predictive analytics project could increase SupplyChainCo's profits through inventory holding gains. Yet, as our study illustrates, the decision of whether or not to implement the project resides upon whether the project will work. We highlight the challenges SupplyChainCo is facing including lack of internal expertise, vendor control, conflicting performance goals, and lack of data.

While the study offered some insights, it has limitations. First, SupplyChainCo is in the chartering phase of its project. A longitudinal study of an analytics implementation from chartering through implementation and six-month follow-up could provide additional insight regarding the issues that companies face when implementing big data projects. Second, we don't know if SupplyChainCo will implement the project. Much of the IS research focuses on approved, successful projects. While it may be possible to identify a few criteria necessary for success (DeLone and McLean 2003), there could be many factors that explain why companies don't implement projects. Yet, our study is unique as we've been involved with the project since the starting point and we do think that even if SupplyChainCo doesn't implement the project there are interesting insights to gain through the journey.

References

Acquisti, A., Friedman, A., and Telang, R. 2006. "Is there a cost to privacy breaches? An event study," *ICIS 2006 Proceedings*, p. 94.

Agarwal, R., and Dhar, V. 2014. "Editorial—Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research," *Information Systems Research* (25:3), pp. 443–448 (doi: 10.1287/isre.2014.0546).

Bose, R. 2009. "Advanced analytics: opportunities and challenges," *Industrial Management & Data Systems* (109:2), pp. 155–172.

Chen, H., Chiang, R. H., and Storey, V. C. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact.," *MIS quarterly* (36:4), pp. 1165–1188.

Dijcks, J. P. 2012. "Oracle: Big data for the enterprise," *Oracle White Paper*.

Dunucci, R. 2016. "Shadow IT: Rampant, Pervasive, and Explosive!," *Cisco Blogs*, January (available at http://blogs.cisco.com/cloud/shadow-it-rampant-pervasive-and-explosive; retrieved February 22, 2016).

Du, S. M., Johnson, R. D., and Keil, M. 2004. "Project management courses in IS graduate programs: What is being taught?," *Journal of Information Systems Education* (15:2), p. 181.

Eisenhardt, K. M. 1989. "Building theories from case study research," *Academy of management review* (14:4), pp. 532–550.

Grossman, T., and Walsh, J. 2004. "Avoiding the Pitfalls of Erp System Implementation," *Information Systems Management* (21:2), pp. 38–42.

Koh, C., Soh, C., and Markus, M. L. 2000. "A process theory approach to analyzing ERP implementation and impacts: the case of Revel Asia," *Journal of Information Technology Cases and Applications* (2:1), pp. 4–23.

Kramer, A. D., Guillory, J. E., and Hancock, J. T. 2014. "Experimental evidence of massive-scale emotional contagion through social networks," *Proceedings of the National Academy of Sciences* (111:24), pp. 8788–8790.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. 2013. "Big data, analytics and the path from insights to value," *MIT Sloan Management Review* (21) (available at http://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/).

Markus, M. L., and Tanis, C. 2000. "The enterprise systems experience-from adoption to success," *Framing the domains of IT research: Glimpsing the future through the past* (173), pp. 207–173.

Marshall, C., and Rossman, G. B. 2011. *Designing qualitative research*, Sage (available at https://books.google.com/books?hl=en&lr=&id=RbqXGjKHALoC&oi=fnd&pg=PR1&dq=designing+qualitative+research&ots=BMjCtjT99Y&sig=M1IvsWMll9ebDcSkGGP1lGORntE).

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., and Barton, D. 2012. "Big data," *The management revolution. Harvard Bus Rev* (90:10), pp. 61–67.

Myers, M. D. 2013. *Qualitative research in business and management*, Sage (available at https://books.google.com/books?hl=en&lr=&id=XZARAgAAQBAJ&oi=fnd&pg=PP2&dq=qualitative+research+in+business+and+management&ots=C9PImr5b9a&sig=cTfY-tZNIzzf9hC_Ky88_TwcMzw).

Philip Chen, C. L., and Zhang, C.-Y. 2014. “Data-intensive applications, challenges, techniques and technologies: A survey on Big Data,” *Information Sciences* (275), pp. 314–347 (doi: 10.1016/j.ins.2014.01.015).

Phua, C., Alahakoon, D., and Lee, V. 2004. “Minority report in fraud detection: classification of skewed data,” *ACM SIGKDD Explorations Newsletter* (6:1), pp. 50–59.

Ross, J. W., and Weill, P. 2002. “Six IT decisions your IT people shouldn’t make,” *Harvard Business Review* (80:11), pp. 84–95.

Shmueli, G., and Koppius, O. 2010. “Predictive analytics in information systems research,” *Robert H. Smith School Research Paper No. RHS*, pp. 06–138.

Tallon, P. P. 2013. “Corporate governance of big data: Perspectives on value, risk, and cost,” *Computer* (46:6), pp. 32–38.

Tallon, P. P., Ramirez, R. V., and Short, J. E. 2013. “The information artifact in IT governance: toward a theory of information governance,” *Journal of Management Information Systems* (30:3), pp. 141–178.

Ward, J. S., and Barker, A. 2013a. “Undefined by data: a survey of big data definitions,” *arXiv preprint arXiv:1309.5821* (available at http://arxiv.org/abs/1309.5821).

Ward, J. S., and Barker, A. 2013b. “Undefined by data: a survey of big data definitions,” *arXiv preprint arXiv:1309.5821* (available at http://arxiv.org/abs/1309.5821).